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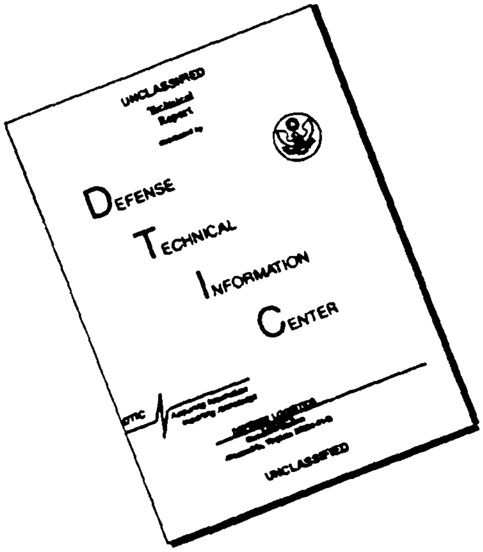
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NEURAL NETWORK CLASSIFICATION OF
MENTAL WORKLOAD CONDITIONS BY
ANALYSIS OF SPONTANEOUS ELECTROENCEPHALOGRAMS

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Arts

By

A-1

GRETCHEN D. LIZZA
B.S.E., The Ohio State University, 1982

1991
Wright State University

WRIGHT STATE UNIVERSITY

SCHOOL OF GRADUATE STUDIES

August, 1991

I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Gretchen D. Lizza ENTITLED Neural Network Classification of Mental Workload Conditions by Analysis of Spontaneous Electroencephalograms BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Arts.

Thesis Director

Department Chair

Committee on
Final Examination

Dean of the School of
Graduate Studies

ABSTRACT

Lizza, Gretchen D. M.A., Applied Behavioral Sciences Program, Wright State University, 1991. Neural Network Classification of Mental Workload Conditions by Analysis of Spontaneous Electroencephalograms.

Artificial neural networks were explored in this study to determine their capability to discriminate workload tasks on the basis of electroencephalograms (EEGs) recorded during task performance. EEG traces were recorded by placing electrodes at the occipital (Oz), parietal (Pz), central (Cz), and frontal (Fz) midline positions during workload tasks. Two conditions of workload were presented to the subjects. The first condition, an eye condition, varied whether eyes were open or closed while subjects counted or sat quietly. In the second condition, the workload conditions presented to the subjects were high and low levels of display monitoring and math processing tasks.

Analyses of variance, discriminant analyses, and an artificial neural network were evaluated for their ability to predict the eight workload tasks using the signal features of EEG traces collected during task performance. The mean log power in five frequency bands, alpha, beta1, beta2, delta, theta, was used to identify the effect of the tasks on the EEG signal. Alpha band effects were primarily reported. Significant differences were shown in the Cz, Pz, and Oz positions for eyes open versus eyes closed effect. Workload tasks showed similar significance at the Cz, Pz, and Oz positions due to the type of task

performed. There were also significant differences due to high and low levels of workload within tasks at the Cz and Pz positions. However, these effects account for less than 6% of the variance as measured by R^2.

Discriminant analyses were used to classify the tasks based on the power from the composite set of frequency bands. Workload tasks were classified correctly 39% of the time and eye tasks had an accuracy of 18%. A neural network was also used to classify the time series EEG signal. Neural network classification was based on multivariate predictors. The neural network was able to classify eye and workload condition tasks with an overall accuracy of 35% for eye tasks and 33.95% for workload tasks.

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This paper is dedicted to my children: Tony, who has fought an immeasureable battle with leukemia during this same period, and Ali, whose laughter and hugs always help me remember the good things life shares.

I. INTRODUCTION

Throughout the past century, technological advances have increased the complexity of machines. Symptomatic of the increased complexity is the exponential growth of controls and displays in fighter aircraft. In the 1940's, the number of switches and controls in the P-51 aircraft was approximately thirty-two. Currently, the F-15 has approximately 305 controls. Not only has the number of controls and displays increased over the past 50 years, but the amount of data presented to the pilot by way of various displays has increased as the systems have become more intricate and complicated. With this increased complexity, the nature of the human interface has shifted from overt physical manipulation of these systems to that of display monitoring. As a result, there is growing emphasis on the need to understand human supervisory control behavior, information processing, mental workload, and other higher order cognitive processes relevant to the design and use of the system.

Characterization of human abilities and limitations in terms of their impact on system performance and mission accomplishment launched efforts to develop automated decision support systems for fighter aircraft. Air Force programs, such as the Pilot's Associate, (Lizza and Friedlander, 1989) and Adaptive Tactical Navigation system (Berning, 1991), have recently produced integrated systems or sophisticated algorithms to help the pilot make more informed decisions. The Pilot's Associate program is directed at integrating several knowledge-based systems resulting in an electronic associate. The primary function of this associate is to monitor the mission situation and pilot actions. The data from this monitoring is analyzed so that the Pilot Associate can provide timely, context-sensitive information to the pilot and to automate essential mission functions when necessary. Optimally, a Pilot's Associate should serve as the mechanism to adaptively distribute tasks needed to control the system to either the human or the machine by determining the available resources of each.

The current configuration of the Pilot's Associate partitions tasks and automation levels with varying degrees of computer aiding. For instance, in some cases the associate suggests alternative decisions based on the current situation or implements corrective action through the navigation system or autopilot. In others, it reconfigures the crew station, or simply informs the pilot of the nature of the problem. (Andes, 1987; Rouse, Geddes, and Curry, 1986).

To implement this flexibility, designers of the system must be able to detect and interpret cockpit input/output variables, human sensory-motor limitations, and the pilot's workload and cognitive resources at any given moment. Before flight, the pilot can tailor the mode, type and quantity of information provided in the cockpit. The overall level of automation can also be preset. During flight, automation levels and some task partitioning may be altered by the Pilot's Associate based on resource modelling. This modelling relies on an application of control theory and information processing models. Aircraft state variables, control input variables, and some subjective workload monitoring are used as basis from which to infer the pilot's state and resource availability. However, the examples of assessment strategies and metrics presented in the Final Report of Phase 1 of the Pilot's Associate Program (Aldern, 1990) are limited in nature (e.g. "the visual resource level represents an estimate of how much the pilot is using his eyes."). Even the measures used to evaluate human resource availability are somewhat vague as described by the report. For instance, it is reported that a resource model computes values for many different pilot resources, such as manual, visual, auditory, and overall. However, neither the model, metrics, nor the measures used are currently specified.

If the Pilot's Associate is to support the pilot as a decision aid and provide responsive levels of automation, then it needs to incorporate models of human cognitive processes and resource limitations into the resource model. As mentioned earlier, characterization of human abilities and limitations in terms of their impact on system performance and mission accomplishment is important for developing or defining variables to be used by a resource modelling module. However, implementation of a theoretical characterization requires an assessment method and reliable indices as well. At this early development stage of the Pilot's Associate, even crude measures may be useful for identifying choke points during the system's operation.

There are several cognitive and information processing models and assessment techniques available for this purpose (Moray, 1979; Navon & Gopher, 1980; Wickens, 1984). In general, these models view the human as having limited resources or capacity to process and respond to information. The term, mental workload, is sometimes used to describe the cognitive loading that is required to perform a task. Under most conditions, an increase in task difficulty leads to an increase in resource expenditure. When task requirements exceed the maximum capacity, there is a performance decrement. The objective of an assessment of workload in the resource model of Pilot's Associate would be to determine existing or potential overload and adjust the level of automation to avoid the performance decrement. Additionally, levels of attention and arousal provide other potential indices of a pilot's mental resources.

The perceptual and cognitive activities of flying an aircraft and performing mission tasks demand sustained attention complicated by the occurrence of infrequent and unpredictable events. Attention is usually defined in terms of vigilance and connotes a conscious processing of information (Kahneman, 1973; Norman & Bobrow, 1975). The source of information may be externally driven by data, or internally driven by memory. Arousal is a distinct, albeit related, concept and is usually defined as a general state varying from coma or drowsiness to alertness or frantic excitement (Duffy, 1962; Lindsey, 1960). These concepts as well as mental workload are integral to the pilot's job of performing a mission.

Researchers studying attention, arousal, and mental workload advocate various methods by which to measure workload. One taxonomy for these methods might be to group the analyses into subjective measures, secondary-task procedures, and physiological measures. Of particular interest to this study is the area of physiological analysis techniques. Physiological techniques attempt to infer the level of mental workload from aspects of physiological response to effort used to perform a task

(Johannsen, Moray, Pew, Rassmussen, Sanders, and Wickens, 1979). One possible physiological measure for inclusion in the Pilot's Associate resource model is electroencephalography (EEG). By monitoring a continuous signal such as the EEG, a Pilot's Associate could continually evaluate the state of the pilot as he or she monitors and operates the system and perhaps it could adjust the level of automation to relieve periods of overload.

Systematic variations in EEG have been noted consequent to changes in physical workload, as well as emotional arousal (Andreassi and Juszczak, 1987; Freeman, 1987; Gevins and Cutillo, 1986; and Landerfield, 1976). Unfortunately, the sensitivity, specificity, and predictive value of the EEG signal has not been conclusively shown to be an indicator of cognitive state. Controversy still remains as to the diagnostic value of the EEG relative to demands on specific resources. (Wickens, 1984; Wilson and O'Donnell, 1987). In 1980, Gevins and Schaffer surveyed the state of the art of psychophysiological research. They concluded that one reason for the variability in the research findings was the possibility that the correlation of spontaneous EEG to cognitive processing could be inherently flawed. An alternate explanation for the lack of definitive findings could be that the interpretive techniques are inappropriate or imprecise. For this reason, an alternate analysis approach to analysis using Analysis of Variance of the difference of the means in the log power of the frequency band of the EEG is sought.

One possible analysis alternative is to use artificial neural network technology. This technology possesses interesting characteristics that led to assessing it as an alternative analysis tool for EEG. Those characteristics are discussed further in the section on neural networks. The present study evaluates a back-propagated neural network's ability to classify EEG traces resulting from arousal and mental workload tasks. The tasks used in this study were selected to represent typical cockpit arousal and workload tasks. A task varying eye state (open or closed) was used to represent arousal levels. The display monitoring and mathematical processing tasks from the Criterion Task Set (CTS) battery (Shingledecker, 1984) were used to manipulate mental workload. The CTS battery was designed to impose demands on the functional information processing resources of human operators.

BRAINWAVE ANALYSIS TECHNIQUES

The human EEG, first reported by Berger in 1929 (cited in Lopes da Silva, 1987), was based on the observation that electrical recordings from the scalp exhibited wave characteristics. These brainwave signals occur spontaneously and are the result of the on-going electrical activity of the brain. A plot of these voltage changes over time is called an electroencephalograph (EEG).

The actual signal is detected by means of surface positioned electrodes. A potential gradient between the skin and the electrolyte (an electrochemical gel) is formed. Because of the large distances between the electrode and the generating brain cells, the EEG signal requires significant amplification, on the order of a factor of 20,000 or more (Barlow, Morton, Ripoche, and Shipton, 1974). Tissue impedance and interference also complicate EEG detection. For instance, physical movement of scalp could vary the positioning of the electrode and disrupt the stability of the recording. Although somewhat difficult, the recording and analysis of the spontaneous brainwave have allowed researchers to detect and collect information with minimum invasiveness. Figure 1 shows typical EEG traces.

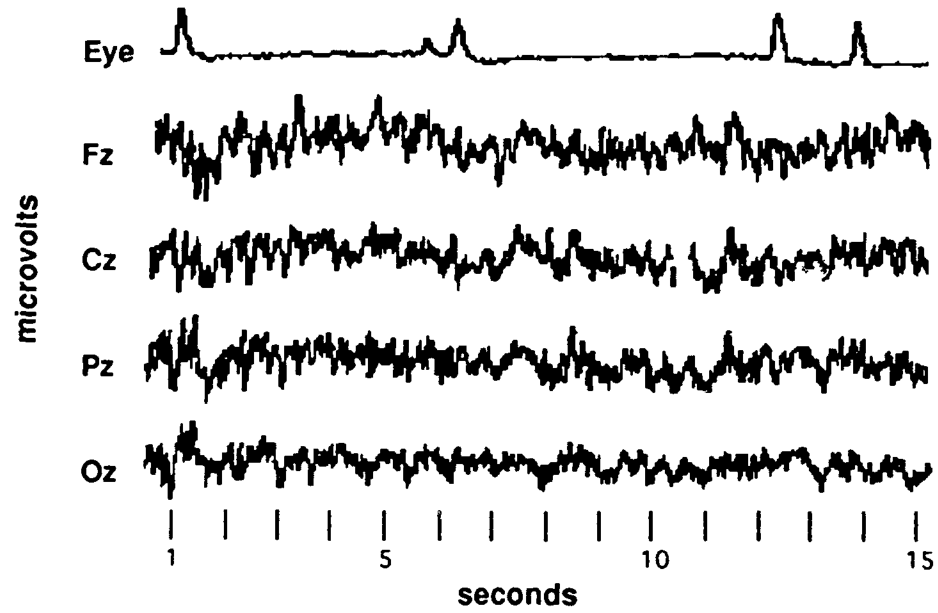

Figure 1
A 15-second, 5-Lead Sample of an Electroencephlogram
Detected During a Math Processing Task

The electrocortical potentials in the EEG are irregular and are generally thought to indicate the electrical integration of multicellular activity. Analysis and interpretation of these spontaneous potential shifts have centered on interpreting their role in gross behavior and correlating variation in these potentials with higher cortical functions (Gevins, 1980).

Frequency Analysis of EEG. Berger (1929) associated the electrical activity of the brain to levels of awareness or conscious states. Using a Fourier transform, Berger analyzed the spectral features of the EEG. By this method, he discovered that there was a disruption of the "alpha train" while subjects performed mental arithmetic. Berger correlated the change in the signal with cognitive functioning.

The Fourier transform, used for spectral analysis of the EEG, is an alternate way of describing the time series EEG in terms of the frequency components of the signal. In the time domain, a continuous function can be represented by the form $h(t) = \int_{-\infty}^{\infty} h(t)e^{2\pi ift}\,dt$, where h is some quantity described as a function of time t. The signal is mapped from the time domain, into a representation of amplitude H. Amplitude H is a function of frequency f, described by the equation $H(f) = \int_{-\infty}^{\infty} H(f)e^{-2\pi ift}\,dt$, for a finite interval of time. If t is measured in seconds, then f is measured in cycles per second or Hertz.

The FFT, a computer implementation of the Fourier transform, is a discrete Fourier transform and is primarily used in EEG research today (Irwin, 1975) . In most cases, the function $h(t)$ is sampled at evenly spaced intervals in time. This spacing is referred to as the sampling rate. The Fourier transform of the time domain into the frequency domain is estimated from a finite number of sample points from the continuous signal. The results of the discrete Fourier analysis are expressed as the amount of power in each component frequency.

Using the FFT analysis techniques, human EEGs are typically classified into four principal frequency bands, called the alpha, beta, delta, and theta bands. The variability and composition of these frequency bands have been investigated as a function of attention/arousal states and workload. Primarily, EEG studies have focused on looking at alpha band activity as the index for attention/arousal. Activity in the alpha band (8-12 HZ) has been found to increase as people relax (Doyle, Orstein, and Galin, 1974). The alpha activity can range from a few microvolts to about 100 microvolts, depending on whether the subject is tense and anxious, or relaxed. Other research on EEG refers to these changes in the alpha band activity as a desynchronization effect. Desynchronization has been related to the effects of the visual/motor manipulation, auditory discrimination, and mental arithmetic (Dolce and Waldeirer, 1974; Giannitrapani, 1975; Walter, 1950). Further, the alpha band activity has also been shown to decrease during visual stimulation, attention, and orienting (Rebert and Low, 1978).

Beta band (13-30 HZ) represents the highest frequencies thought to be significant in EEG. Thompson and Thompson (1965), analyzed EEG activity during verbal learning in a series of experiments but they concluded that the beta band effects were primarily related to focused attention. Other research has suggested that beta band activity is found to increase during focused attention merely because it becomes more visible as alpha frequencies are blocked (Freedman, Hafer, and Daniel, 1966). These results indicate that beta band activity may be affected by tactile, auditory, and emotional stimulation. Beta has the largest band width of the four principal frequency components of the spectra. For this reason, some researchers have split the beta band into two ranges, referred to as beta1 and beta2. The lower beta range is thought to have less contamination due to muscle artifacts and to be better correlated with mental workload (G. Wilson, personal communication, 10 May 1991).

Studies have reported decreased theta (4-7 HZ) and delta (below 4 HZ) band activity during high arousal or stress. These lower frequency rhythms have also been reported as being common during unconsciousness, regardless of whether the state is due to sleep, anesthesia, cranial trauma, or a convulsive seizure. (Burch, Dossett, Vorderman, and Lester, 1967).

In 1980, Gevins and Schaffer critically reviewed studies using EEG correlates of performance on cognitive tasks. They categorized EEG research into two groups: 1) studies that attempted to define the functional topography of electrocortical activity with complex tasks, and 2) studies that manipulated complexity or difficulty of tasks. The first category focuses on brain mapping. That is, relating cognitive activity to specific areas or regions of the brain. The second category of studies is designed to determine the diagnosticity or sensitivity of the EEG to cognitive activity. It is the second category that is of interest in attempting to build the resource modelling capability for the Pilot's Associate.

However, their summary of the state-of-the-art of this paradigm was not encouraging. Gevins and Schaffer stated that although it would appear that the degree of EEG desynchronization would be directly related to degree of task difficulty, none of the studies in their review, except one by Gale (1978), had adequately quantified this relationship. They further revealed that almost all other studies have been flawed by confounding manipulation of task difficulty with other uncontrolled factors or by inadequate or ambiguous EEG analyses. Wilson and O'Donnell (1987) also concluded in an overview paper that one single physiological measure may not be sensitive to the multi-dimensional nature of workload. Further, they suggest that measurement montages might provide more sensitivity, and as a set, may even prove to be diagnostic.

Even within a montage, the individual measures must be reliable and sensitive. EEG has not been shown to be either. The lack of information about the source and composition of the EEG signal may shed light on why there has been minimal success in correlating the EEG with cognitive activity using current analysis strategies. Recent postulates about the EEG signal (Papnicolaou and Johnstone, 1984) hold that the brain's electrical responses are reflective of: 1) the interaction between the organic peculiarities of the brain tissue; 2) the automatic brain operation for maintaining bodily functions; 3) the amount and type of sensor signals; and 4) the information processing operations at any given moment. If these postulates are accurate, the EEG signal is produced by many physical, automatic, and cognitive processes. The electrical properties of these activities and their integration, as seen in the resultant EEG signal, are not well understood.

Papnicolaou, Johnstone, and Freeman proposed more integrated theories of the brain's electrical response. Skarda and Freeman's (1987) description of the ensemble activity of the brain as a form of time varying spatial patterns also supports a view of brain function that requires a multivariate, pattern recognition approach to EEG analysis. He hypothesized that the brain's activity behaves in a self-organized process of adaptive interaction with the environment. These theories call into question the value of linear signal processing as an analysis tool for EEG.

Spectral analysis, which is the signal processing technique used primarily in EEG analysis, makes assumptions about the linearity of a signal and uses a statistical sampling processes. Schmitt, Dev, and Smith (1976), and Lopes da Silva (1987) concluded in their general reviews, that research based on spectral analysis has attributed too many functions to the alpha and other bands of the EEG. Lopes da Silva analyzed the signal processing aspects of EEG research. His discussions of the loss of phase information when using Fourier transformation and the problems with establishing an optimum period of analysis suggest that the current analysis techniques are limited, or possibly inappropriate, and that more sophisticated approaches such as multidimensional, nonlinear, parallel signal processing may provide better tools for indexing the brain's functions. However, if the goal is to interpret the EEG, or more importantly, to find reliable indices of the effects of workload, then even the most comprehensive computational approaches may not be sufficient because they may not adequately reflect the nature of the neural system itself.

One class of connectionist neural models may provide an alternative to the statistical approaches previously taken. In their hardware/software form, these models are sometimes referred to as artificial neural networks or simply neural networks. Over the last 25 units are organized into layers and each layer sends signals to, and receives signals from, other layers. The state of the nodes at each layer results from a synthesis of the states of the other layers from which it receives input. The computational model is distributed rather than serial.

The purpose of this effort is to determine the utility of neural networks for EEG research and analysis. The study is focused on investigating the ability of a neural network to categorize arousal and workload tasks based on information in the EEG signal itself. The advantage of this approach is that a classification of the tasks is directly output from the neural network.

Classification by the neural network revolves around resemblance. That is, if the EEG pattern from a particular task, A, resembles the previously presented patterns from that task, more than any other task, then it resembles the task pattern enough to be classified as task A, also. This process of classification is sometimes referred to as pattern recognition or mapping. It is this emulation of pattern recognition schema or mapping approximation capabilities that distinguishes neural networks from other architectures.

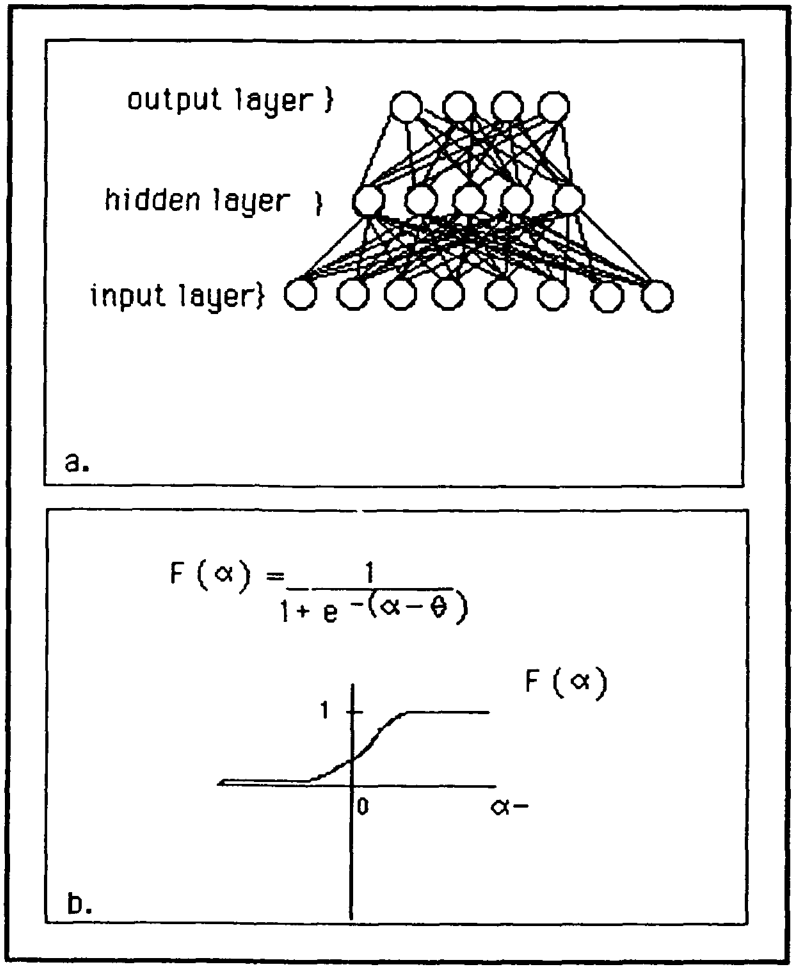

Figure 2
Hidden Layer Perceptron with *N* Continuous Valued Inputs and Sigmoid Nonlinearity Function

<u>Network Architecture.</u> The uniqueness of neural network technology is in the architecture. Neural network architecture is specified by net topology, node characteristics, and training or learning rules. This study evaluates a hidden-layer, backpropagated perceptron. A perceptron consists of processing elements, which are interconnected with

unidirectional signal channels called connections. A node is a simple unit processor and is the basic element of the perceptron. In this study, the nodes are analog and non-linear. Parallel input values, (e.g. amplitude), arrive at the first layer of nodes via a preset number of input connections. Each connection can be binary or can vary over a large range for the continuous-valued input. The static and dynamic relationship of all the nodes and their interconnections is trained by presenting a number of samples of the signal and relating those samples to the desired response.

The nodes can be thought of as short term memory or threshold logic units. The input values arriving at each node form a situation feature vector $A = (a_1, \ldots, a_i)$. The weights between all i nodes and the jth output node can be represented as a vector W_j, where $W_j = (w_{1j}, \ldots w_{ij})$, and where w_{ij} represents the connection strength between the ith node input and the jth node output strength (r_{sj}), which is the response unit. The weights (w_{ij}) can be thought of as similar to long term memory. A threshold function is used to scale the output value of a node. A nonlinear sigmoid function used as the nodal threshold fuction can be found in Figure 2b. The sigmoid threshold function determines how closely a new input pattern must match in order for it to be classified as another exemplar of a particular task. When the value of the sigmoid is near one, there must be a close match. A lesser value allows a poorer match. A new sample is either accepted as a match or becomes a new class.

The network connections are given default weights initially which are then refined through an algorithm called backpropogation, an application of a delta or chain-rule (Hecht-Nielsen, 1990). The algorithm is said to supervise the weight adjustment, called training of the network, so that noise in the input sample becomes less relevant as more samples or training passes are presented to the net. In the backpropagation strategy, the network's operation consists of two sweeps. The first is a forward sweep where the input is propagated through each layer adjusting the weights towards the final desired output value. Then the actual output is compared to the desired output. The difference between the actual and desired output is calculated. An error correction based on the difference is then propagated back through the layers to update the weights and refine the node summation process for future input.

The input vector used in the present study was comprised of the digitized EEG time histories collected from subjects during performance of the tasks. The goal of this effort was to train the neural network until it converged to a stable characterization of eight workload tasks. This was achieved by presenting the neural network representative EEG samples from each task and assigning each sample with a number representing the task. For example, a sample from an eyes closed task was presented to the neural network and assigned the task number 1; whereas, a sample from the eyes open task was given the task number 2. As more samples of each task were related to their specific number label, the net developed weighting values based on like features of the samples. This reduced the noise or the signal features which were not consistent across the samples. In essence, the neural network refined its link weightings based on signal consistency within each task.

Eventually, it converged on an optimum weight for each task by maximizing the similarity within a task and the differences between the tasks. Once stable, the network was then presented new samples from the tasks and its ability to correctly classify the samples by task was evaluated.

Rationale and Hypotheses. This study was motivated by the need to find meaningful parameters relating EEG activity and cognitive processes at a macro level to provide reliable indices of workload to systems such as the Pilot's Associate. Based on the discussion of current EEG research, there appears to be no reliable method producing valid indices for this purpose. Neural networks were investigated as an alternative to classical analysis techniques.

The parallel nature of the neural network provides sufficient rationale for investigating this technology as a new method for investigating EEG as a source of information about cognitive processes. But, the most compelling feature of the net was its potential ability to classify signals with low signal-to-noise ratio. Neural network's have been shown to estimate a consistent signal and enhance the distinguishing feature of the signal (Honenberger and DasGupta 1989; Kohonen, Barna, and Chrisley, 1988; Tamura and Waibel, 1988). Signal enhancement within a noisy feature set is particularly useful since little is understood about the composition of the EEG signal. The neural network approach may be viewed as a noise reduction strategy. Another advantage of neural network signal analysis is that these systems make no prior assumptions about the statistical properties of the signal. If there is meaningful and usable information in the EEG resulting from work or thought, mapping from a set of noisy signals to that of noise-free stable response should provide a way of finding it.

The hypothesis for this study is: If artificial neural network techniques provide a parallel processing signal processing capability for signals in the time-space domain, then these systems will provide a sensitive tool for classifying on the basis of variations of workload the multidimensional signal of the EEG.

This study uses an artificial neural network to classify workload related EEG time histories. It compares the classification performance of a neural network to the traditional FFT analysis used to analyze EEG/workload paradigms. Specifically, the following questions were addressed:

1) How sensitive is an FFT in its ability to discriminate levels of workload?

2) How sensitive and diagnostic is discriminant analysis based on spectral features?

3) What level of sensitivity does a neural network have for the same tasks using temporal data?

In order to answer these questions, standard arousal and cognitive performance tasks with two levels of difficulty were used to provide known levels of performance. Time histories of EEG were collected and digitized while subjects performed various workload tasks. An FFT was used to transform the digitized data into the frequency domain. Data were then analyzed using ANOVA and discriminant analysis. Neural networks were configured and trained on half the available EEG data. The remaining half of the data were used to test the abilility of the neural network to classify arousal and workload tasks and difficulty levels of these tasks.

II. METHOD

SUBJECTS

Subjects were eight men and women who had experience with physiological experiments similar to the current study and were paid for their participation. Age ranged from 20 to 35 (mean = 24) years. All subjects reported having normal or corrected to normal visual acuity (from 20/20 to 20/40). The subjects were screened for special medical problems. All subjects reported they had not used medication, drugs, or stimulants, including caffeine the morning of the experiment.

APPARATUS

Display. A Commodore 64 computer and color video monitor (Commodore model 1702) were used to generate the mathematical and display monitoring tasks. The keypad was made up of four buttons in a north, south, east, west configuration.

EEG equipment. Beckman silver chloride surface electrodes were placed at the occipital (Oz), parietal (Pz), central (Cz), and frontal (Fz) midline positions. The positions were located as per the International 10-20 placement positions standard (Jasper, 1958). An additional electrode was placed over the right eyebrow for eyeblink artifact rejection. Mastoid electrodes served to provide a reference and electrical ground for the subject. All equipment was inspected by the safety office of the Armstrong Aerospace Medical Research Laboratory, Wright Patterson AFB, Dayton, Ohio. All hardware, including the actual point of contact with the electrode leads, to the electrical amplifier connections, were approved for human use. No adverse reactions were encountered with this equipment. Subjects were assured that if displeasure or discomfort was experienced, they were free to terminate exposure without penalty (Appendix A).

Amplification. Signals were amplified fifty thousand times by Grass P511 amplifiers. The signals were processed through a bandpass filter of 0.10 to 30 HZ and notch filtered at 60 HZ to reduce noise from power line oscillations around this frequency.

TASK CONDITIONS

Two manipulations were defined for this study, a set of eye conditions and a separate set of workload conditions. Four tasks were developed for the eye manipulation and four tasks were developed for the workload manipulation, producing total of eight different conditions overall. As noted before, these tasks were selected because they represent the types of tasks in a cockpit and are commonly used in arousal and workload research paradigms.

Eye Condition. Four tasks that constituted the eye condition were formed by the factorial combination of two variables, counting and eye status. Subjects either counted silently, or did not count during both an eyes-open and an eyes-closed condition. Prior to the no-counting tasks subjects were asked to relax, blank their minds and during the eyes-closed condition they were asked to keep their eyes closed for the entire three minutes. The room was darkened for these conditions. For counting tasks, the subjects were asked to count backwards from 1000 by sevens to insure consistent tasking across the eyes-open/eyes-closed conditions.

Workload Condition. Four conditions were used for the workload manipulation. These were two levels of difficulty for a mathematical processing task and two levels of difficulty for a display monitoring task. The mathematical processing task from the Criterion Task Set was used. The subjects were required to solve a number of simple addition and subtraction problems and determine whether the answer was greater or less than five. Subjects then used a designated key to indicate the response. No problem had an answer equal to five. Practice effects were minimized by five practice trials at each level prior to EEG collection.

Two levels of workload were presented. A low workload task consisted of mathematical operation problems requiring addition or subtraction of two numbers. A high workload level required the subjects to perform three operations in each problem (e.g. 4+3-2+3 or 9-6-1+4). The sequence of numbers added and subtracted did not result in numbers less than 0. Performance measures of reaction time and accuracy were recorded. Subjects were instructed to perform as quickly and accurately as possible. Accuracy rates of 85% were acceptable. After the first, three minute run, the subjects were given performance feedback to insure an acceptable speed/accuracy trade off.

Problems appeared one at a time and were experimenter-paced. Therefore, the number of problems did not vary. Stimuli was presented at a fixed rate of 1 problem every 3.5 seconds. Subjects had to respond before the next equation was presented. The subjects were instructed to be as quick and as accurate as possible. The problems were presented in two trial blocks for three minutes at each level.

Subjects were also given a standardized loading task designed to place variable demands on their visual perceptual information processing resources. The CTS display monitoring task used in this experiment is based on a probability monitoring paradigm developed by Chiles (1968). The subjects performed at two levels of workload, low and high, for the tasks. Low workload consisted of one dial represented on the screen. The high workload level had three dials.

Subjects were asked to monitor computer generated displays which represented electromechanical dials. Each dial was represented by a numbered rectangular box consisting of six vertical hashmarks and always appeared in the same position on the monitor. A pointer positioned below the six marks moved randomly to each position with equal probability. This position was updated at a rate of two moves per second. At some point, one of the pointers began to move in a prescribed pattern and stayed on one side of the dial more than the other. This nonrandom movement served as the signal. The subjects' task was to identify a signal. In the low workload condition, this corresponded to a yes/no decision. In the high workload level, the subject had to decide which dial contained the signal. When the signal was detected, a key on the computer keypad that corresponded to the dial showing a signal was pressed. The signal recognition had a default of 30 seconds. Only one dial exhibited a signal for any given trial. The signal lasted 30 seconds and occurred over 60 pointer moves. Subjects were instructed that there would be two or three signals per period. Twenty-five seconds separated signal onset after the previous signal had been recognized. Subjects were familiarized, via practice trials, with all levels prior to data collection. Instructions to the subjects emphasized certainty in signal detection to minimize false positive identifications. Performance measures of reaction time for correctly identified signals, missed signals, and false alarms (signals identified when no signal is present) were recorded. After the first three minute trial, subjects were given performance feedback.

PROCEDURE

The experiment was run over a two day period. The first day, served as an introduction and familiarization day. Subjects were fitted with EEG electrodes. Each subject was given five practice trials for each level of the mathematical and probability monitoring tasks. During these trials, the subjects fixated on a small dot in the center of the display. A ready signal was given by the experimenter and subjects initiated the tasks by pressing a start switch. Questions regarding the CTS tasks, use of the keypad, and performance levels were answered and problems were resolved at that time.

The second day was used for data collection. Subjects were seated in a sound-attenuated, electrically shielded test booth, designed especially for physiological measurement. They were instructed to relax. The schedule and all tasks were reviewed with each subject. EEG electrodes were applied and the subjects were asked if they were comfortable and ready to start. Individual task instructions were given before each task and questions were answered. Each trial was three minutes in duration with approximately a minute rest between runs.

For no-counting condition trials, each subject was directed to relax and leave eyes closed, (or opened), through the entire three minute trial. For counting conditions, subjects were instructed to concentrate only on the counting task and to count silently by sevens, backward. The subjects used their own pace and were required to begin at 1000 again if they make a mistake. Subjects were instructed that in the event the "0" is reached before the three minutes were up to begin the count again. Subjects began counting backwards from 1000 upon a "begin" signal by the experimenter.

For the CTS tasks, the experimenter gave each subject a ready signal and runs were initiated by the experimenter pressing the start switch. Procedures were the same as used during practice trials. Each subject received all levels of all tasks. The order of presentation for the eight conditions (eyes open, eyes closed, eyes open-counting, eyes closed-counting, math processing-high, math processing-low, display monitoring-high, display monitoring-low) was based on a Latin Squares Design (Appendix D). Two eight by eight Latin squares were used to randomize presentations for each run. Each condition was given twice, as first or second presentation in a pair of conditions. This was done to avoid the confounding effect of the order of presentation.

EEG Signal Conditioning. Data resulting from the experiment were 16 three-minute time histories of the EEG per subject. These resulted from the eight tasks repeated twice per subject. All data were collected on-line while subjects were performing the tasks. Segments of time histories with artifacts were eliminated from selection for the analysis. Artifacts such as muscle electrical potential which cluster at the high beta band (Gevins and Remond, 1987), eyeblinks at the 1-5 HZ range (EOG), head and body movements, perspiration, and low frequency instrumental artifacts under 1 HZ have been traditionally seen as contaminates and removed from the data. The raw analog EEG data were screened for these artifacts in order to provide a "clean signal" for analysis. For each of the three minute trials, at least 100 seconds of the 180 second task time was needed to be relatively artifact free to consider the data usable for the analysis. This criterion was met for all subjects for all tasks.

The identification and removal of artifacts was based both on an automated eyeblink rejection algorithm and upon expert judgement of supervising laboratory personnel. Gevins (1980) compared automated artifact rejection algorithms to consensus expert judgement. The algorithms were able to identify only 65% of the 229 events noted by the experts. In addition, 27% of the algorithm's detections were false positive. In view of these findings, by combining both algorithmic and expert opinion the reliability of the resultant data were enhanced. By reducing the number of artifacts through the EOG transform algorithm, ideally, 128 times histories with only a few sections missing would have been generated from this experiment. Only one session from one subject was considered unusable. Therefore, 120 time histories were used for the analyses.

The data from this study were subjected to two different analysis techniques, that of classical statistical methods and by neural network analysis. Data conditioning of the data for the these analysis required two different procedures. Those procedures are outlined in the Results section for each analysis technique.

III. RESULTS

Data were analyzed using ANOVA of the spectral features. This analysis was used to compare the sensitivity of the neural network to that of the FFT sensitivity. The process of the analyses was as follows: 1) an FFT was performed to convert the EEG signal into its component spectral features; 2) Analysis of Variance techniques were then used on spectral features of the data to establish the baseline sensitivity of the spectral features; 3) Discriminant analysis was used to classify the eight tasks so that performance based on statistical analysis using spectral features could be compared to the neural network's discriminative capability based on full signal features; 4) An artificial neural net was used to discriminate between the eight tasks. The input to the neural network was the full signal features of the EEG time histories resulting from the tasks.

Results of ANOVA analysis are reported first, followed by the results of the discriminant analysis. Finally, the results of three configurations of the neural network are presented. Initial configuration was a 800 x 100 x 8 three layer perceptron. Because of the inability to converge at this configuration, a 800 x 250 x 8 network was trained and tested. Poor performance at this configuration led to a third attempt on a 800 x 300 x 8 network. The results in this study are based on the third and final network configuration.

FFT ANALYSIS OF VARIANCE

ANOVA was used to analyze the effect of workload tasks on the log power of the alpha, beta1, beta2, delta, and theta frequency bands. This approach is used traditionally for EEG studies. FFT was used to estimate the power in each frequency band. The mean log power for each of the bands and forty ANOVA's are summarized in Tables 1 and 2, respectively. There is one ANOVA for each combination of the two conditions (eye, workload), 5 frequency bands (alpha, beta1, beta2, delta, theta) and 4 electrode positions (Fz, Cz, Pz, Oz). The dependent variable in each ANOVA was the log power at a particular combination of the 5 bands and four electrode positions. The analysis was done across sessions.

For the purposes of this study, the effect of the tasks on the activity in the alpha band was of primarily interest for the ANOVA technique. The remaining four bands were also analyzed and the results can be obtained by reviewing Tables 1 thru 4.

The mean log power for each band and lead combination for the eye condition can be found in Table 1. Inspection of Table 1 shows that overall, the effect of whether subject's eyes were opened or closed was reflected in the difference of the log power in the alpha, beta2, and theta bands.

Table 1.
Mean Frequency Log Power Values for
Each Lead During Eye Conditions

Eye Condition (Open/Closed):

Bands	Fz closed	Fz open	Fz diff	Cz closed	Cz open	Cz diff	Pz closed	Pz open	Pz diff	Oz closed	Oz open	Oz diff
alpha	-0.812	-0.682	-0.130	1.552	1.175	0.377	1.307	1.088	0.219	1.395	1.146	0.259
beta1	-1.421	-1.322	-0.099	0.676	0.497	0.179	0.607	0.521	0.086	0.771	0.656	0.115
beta2	-1.573	-1.528	-0.045	0.478	0.190	0.280	0.436	0.284	0.152	0.604	0.412	0.192
delta	0.060	1.239	-1.179	0.172	0.170	0.025	1.722	1.722	0.000	1.831	1.870	0.039
theta	-0.605	0.213	-0.819	1.420	1.270	0.150	1.466	1.391	0.075	1.675	1.588	0.088

Counting Tasks (Counting/No-Counting):

Bands	Fz no cnt	Fz count	Fz diff	Cz no cnt	Cz count	Cz diff	Pz no cnt	Pz count	Pz diff	Oz no cnt	Oz count	Oz diff
alpha	-0.745	-0.004	0.075	1.348	1.379	-0.032	1.181	1.214	-0.033	1.271	1.269	0.001
beta 1	-1.374	0.005	0.079	0.608	0.565	0.043	0.577	0.551	0.026	0.729	0.697	0.032
beta2	-1.546	-0.100	0.064	0.326	0.341	-0.015	0.343	0.377	-0.034	0.510	0.505	0.005
delta	0.629	0.042	0.263	1.702	1.720	-0.018	1.697	1.747	-0.049	1.855	1.846	0.009
theta	-0.187	-0.180	0.253	1.355	1.334	0.021	1.410	1.447	-0.036	1.573	1.690	-0.117

The ANOVA results in Table 2 show that the differences in the log power for alpha for the Cz ($p = 0.002$), Pz ($p = 0.032$), and Oz ($p = 0.017$) electrode positions were significant at the 5% level of confidence. The proportion of variance accounted for the main effect of the eye condition can also be found in Table 2. For the significant alpha band, (Cz, Pz, Oz) effects, the R^2 were 0.20, 0.11, and 0.17 respectively. The Cz lead showed significance in all bands, except delta for the eye tasks. Overall, the effect of eyes open or closed were significant eleven out of the twenty analyses. Those effects were distributed through the frequency bands and at all leads. However, R^2 showed that only 18% of the variation was accounted for in all cases.

Table 2.
ANOVA Results For Eye Condition

Eye Condition (Open/Closed):

	F Statistics				**P Value**				**R^2**			
Bands	**Fz**	**Cz**	**Pz**	**Oz**	**Fz**	**Cz**	**Pz**	**Oz**	**Fz**	**Cz**	**Pz**	**Oz**
alpha	0.666	24.453	7.081	9.778	0.442	***0.002***	***0.032***	***0.017***	0.038	0.204	0.113	0.172
beta1	0.814	15.968	5.285	4.897	0.397	***0.005***	0.055	0.063	0.034	0.077	0.017	0.037
beta2	0.175	24.265	6.457	11.256	0.689	***0.002***	***0.039***	***0.012***	0.005	0.104	0.029	0.062
delta	60.280	0.560	0.000	0.792	***0.000***	0.479	1.000	0.403	0.640	0.007	0.000	0.014
theta	31.003	32.753	2.387	5.584	***0.001***	0.***001***	0.166	***0.050***	0.558	0.182	0.043	0.040

Counting Tasks (Counting/No-counting):

	F Statistics				**P Value**				**R^2**			
Bands	**Fz**	**Cz**	**Pz**	**Oz**	**Fz**	**Cz**	**Pz**	**Oz**	**Fz**	**Cz**	**Pz**	**Oz**
alpha	0.018	0.520	0.764	0.007	0.895	0.495	0.411	0.935	0.000	0.002	0.003	0.000
beta1	0.038	6.360	0.286	3.168	0.850	***0.039***	0.609	0.118	0.000	0.004	0.002	0.003
beta2	0.179	0.676	0.287	0.058	0.685	0.407	0.608	0.817	0.000	0.000	0.001	0.000
delta	0.201	1.126	2.703	0.108	0.668	0.324	0.144	0.752	0.001	0.003	0.024	0.001
theta	0.042	0.780	1.132	7.862	0.844	0.406	0.323	***0.026***	0.000	0.004	0.010	0.071

Interaction:

	F Statistics				**P Value**				**R^2**			
Bands	**Fz**	**Cz**	**Pz**	**Oz**	**Fz**	**Cz**	**Pz**	**Oz**	**Fz**	**Cz**	**Pz**	**Oz**
alpha	7.992	0.812	0.166	3.382	***0.026***	0.398	0.696	0.109	0.005	0.001	0.001	0.001
beta1	0.004	0.243	0.783	0.704	0.954	0.637	0.406	0.429	0.000	0.001	0.010	0.002
beta2	0.021	0.158	0.755	0.666	0.889	0.702	0.414	0.441	0.000	0.001	0.009	0.002
delta	2.117	0.083	1.160	0.284	0.189	0.782	0.317	0.611	0.009	0.000	0.014	0.002
theta	0.714	1.860	1.598	0.035	0.426	0.215	0.247	0.857	0.002	0.009	0.017	0.000

The mean log power for each band and lead combination for the counting task can be found in Table 1. The ANOVA results are given in Table 2. Inspection of Table 2 shows that, the effect of counting versus no counting was only significant for the differences in log power of beta1 at the Cz lead and theta at Oz at the 5% level of confidence. By inspecting Table 2 it can be seen that the only significant interaction involving the alpha band was at the Fz position, $p < 0.02$. However, this interaction accounted for less than 0.5% of the variation based on the R^2 for this effect. No interaction accounted for more than 2% of the proportion of the variance.

The mean log power for each band and lead combination for the workload conditions can be found in Table 3. The ANOVA results are given in Table 4. Inspection of Table 4 shows that the effect of whether subjects were performing in the math processing or a display monitoring condition was significant with respect to changes of the log power of the alpha band. Alphas for the Cz, Pz, and Oz electrode positions were significant at the p = 0.05 level or better. The effect of task was widespread and seen on all frequency bands. In all, twelve of the 20 effects were statistically significant at the 5% level of confidence. The log power of alpha at the Fz position was not significant. Beta1 was significant at the 5% level of confidence at the Cz, Pz and Oz leads as well. Beta2, delta and theta were significant at the Cz lead and all bands were significant at the 5% level of confidence on the Oz lead except theta.

Table 3.
Mean Frequency Power Values for
Each Lead During Workload Condition

Display Monitoring/Math Processing:

	Fz			Cz			Pz			Oz		
Bands	DM	MP	diff	DM	MP	diff	DM	MP	diff	DM	MP	diff
alpha	-0.639	-0.534	-0.106	1.050	1.164	-0.114	0.977	1.066	-0.089	1.131	1.199	-0.069
beta1	-1.260	-1.147	-0.113	0.470	0.554	-0.083	0.459	0.562	-0.102	0.651	0.758	-0.107
beta2	-0.145	-1.362	-0.087	0.098	0.195	-0.097	0.191	0.241	-0.050	0.352	0.437	-0.085
delta	1.135	1.423	-0.287	1.717	1.769	-0.052	1.721	1.753	-0.033	1.852	1.897	-0.045
theta	0.285	0.464	-1.790	1.338	1.329	0.009	1.415	1.407	0.008	1.627	1.648	-0.021

Level of Difficulty (High/Low):

	Fz			Cz			Pz			Oz		
Bands	high	low	diff	high	low	diff	high	low	diff	high	low	diff
alpha	-0.606	-0.567	0.133	1.061	1.153	-0.092	0.991	1.052	-0.061	1.151	1.179	-0.027
beta 1	-1.237	-0.067	0.181	0.492	0.532	-0.040	0.488	0.533	-0.045	0.687	0.721	-0.034
beta2	-1.419	-0.027	0.361	0.153	0.140	0.013	0.224	0.207	0.017	0.390	0.398	-0.008
delta	1.229	-0.100	0.261	1.739	1.746	-0.007	1.739	1.734	0.005	1.872	1.877	-0.004
theta	0.363	-0.023	0.327	1.326	1.341	-0.015	1.402	1.420	-0.018	1.647	1.628	0.019

Inspection of Table 4 shows that overall, the effect of whether subjects were performing at the high or low level of a particular condition was significant for the Cz and Pz electrode positions at the p = 0.05 level or better. Only four band/lead combinations were significant for the level of difficulty analysis. Those were alpha at Cz and Pz ($p = 0.008$, 0.006 respectively), beta1 at Cz ($p = 0.006$), and theta at Pz ($p = 0.010$). However, the proportion of variance explained by any of these effects was less than 6% in all cases.

Inspection of Table 4 reveals that the only significant interaction involving the alpha band was at the Pz position, $p < 0.025$. However, this interaction only accounted for less than 2% of the variation based on the R^2 for this effect as shown in Table 4. Theta was significant at the Cz and Pz leads. Further inspection of Table 4 reveals that no interaction accounted for more than 2% of the variation.

Table 4.
ANOVA Results For Workload Condition

Display Monitoring/Math Processing:

	F Statistics				**P Value**				**R^2**			
Bands	Fz	Cz	Pz	Oz	Fz	Cz	Pz	Oz	Fz	Cz	Pz	Oz
alpha	2.958	13.791	7.086	14.992	0.129	0.006	0.032	0.006	0.021	0.072	0.063	0.030
beta1	4.486	10.654	21.224	31.821	0.072	0.029	0.025	0.001	0.056	0.026	0.049	0.057
beta2	3.301	5.523	2.563	7.469	0.112	0.014	0.153	0.029	0.036	0.018	0.006	0.022
delta	18.080	7.690	2.384	11.621	0.004	0.005	0.166	0.011	0.067	0.035	0.017	0.026
theta	9.486	0.076	0.059	0.951	0.108	0.028	0.815	0.362	0.036	0.001	0.001	0.004

Level of Difficulty (High/Low):

	F Statistics				**P Value**				**R^2**			
Bands	Fz	Cz	Pz	Oz	Fz	Cz	Pz	Oz	Fz	Cz	Pz	Oz
alpha	0.421	13.293	0.153	3.066	0.537	0.008	0.006	0.124	0.003	0.046	0.063	0.030
beta1	2.011	15.359	0.153	3.698	0.199	0.006	0.502	0.096	0.020	0.006	0.049	0.057
beta2	0.177	0.654	0.501	0.261	0.687	0.445	0.475	0.625	0.003	0.000	0.006	0.022
delta	0.615	0.403	0.572	0.032	0.459	0.546	0.276	0.862	0.008	0.001	0.017	0.026
theta	0.065	0.472	1.392	0.618	0.807	0.514	0.010	0.458	0.001	0.003	0.001	0.004

Interaction:

	F Statistics				**P Value**				**R^2**			
Bands	Fz	Cz	Pz	Oz	Fz	Cz	Pz	Oz	Fz	Cz	Pz	Oz
alpha	1.018	1.952	8.015	2.962	0.345	0.205	0.025	0.219	0.005	0.006	0.018	0.006
beta1	0.065	1.259	2.519	0.012	0.806	0.299	0.157	0.915	0.000	0.001	0.001	0.000
beta2	0.010	0.189	1.766	0.002	0.921	0.677	0.226	0.965	0.000	0.000	0.003	0.000
delta	0.194	0.191	0.075	2.582	0.673	0.675	0.792	0.152	0.001	0.001	0.000	0.014
theta	0.437	0.065	8.714	3.382	0.530	0.038	0.021	0.109	0.002	0.015	0.013	0.006

DISCRIMINANT ANALYSIS

Discriminant analysis was used to classify the eight tasks based on the log power in the bands of the spectra. Two separate analyses were performed. The first used the log power from all frequency bands and the second used only the alpha band log power as input. Within each of these two general discriminant analyses, three different analyses were performed. These analyses varied the cell size and whether the derived disriminant function was used to discriminate novel stimuli.

Each discriminant function was developed using all eight conditions as a set so that the results were similar to the output of the neural net. For the first analysis, data from both experimental sessions were used. One session from one subject was unavailable for analysis, therefore, n = 15. Once a discriminant function was developed, the input data were then used as the test set to evaluate the robustness of the derived function. This analysis is most analogous to the training versus training results discussed in the neural network performance section. These results can be found in Table 5.

Table 5 is made up of six, two by two cells, one set for each level of analysis (n = 15, n = 8, and n = 7). Entries in the cells represent the percent correct classification of the conditions by the discriminant function. Although all eight conditions were included in the matrix, eye condition and workload have been broken out separately in the presentation of the data to be consistent with the ANOVA design. The margins of the cells represent the average percent classification across the levels and types of tasks. The corner value is the overall percent correct classification for the condition. Inspection of Table 5 shows that using all the available features of the spectra for n =15, the discriminant function actually correctly classified all of the tasks.

Table 5.
Discriminant Analysis Table
Percent Correct Classification of Tasks Using 5 Bands, 4 Leads

N = 15

EYE

	CLOSED	OPEN	
COUNT	100.00 **1**	100.00 **1**	100.00
NO COUNT	100.00 **1**	100.00 **1**	100.00
	100.00	100.00	**100.00**

WORKLOAD

	DM	MP	
HIGH	100.00 **1**	100.00 **1**	100.00
LOW	100.00 **1**	100.00 **1**	100.00
	100.00	100.00	**100.00**

N = 8

EYE

	CLOSED	OPEN	
COUNT	87.50 **7**	100.00 **8**	93.75
NO COUNT	87.50 **7**	100.00 **8**	93.75
	87.50	100.00	**93.75**

WORKLOAD

	DM	MP	
HIGH	100.00 **8**	87.50 **7**	93.75
LOW	100.00 **8**	100.00 **8**	100.00
	100.00	93.75	**96.88**

N = 7

EYE

	CLOSED	OPEN	
COUNT	28.57 **2**	0.00 **0**	28.57
NO COUNT	28.57 **2**	14.29 **1**	21.43
	28.57	14.29	**17.86**

WORKLOAD

	DM	MP	
HIGH	28.57 **2**	28.57 **2**	28.57
LOW	14.29 **1**	85.71 **6**	50.00
	21.43	57.14	**39.29**

The second discriminant analysis used only the data from session 1 to develop a discriminant function. Hence, only eight observations were used. The discriminant function derived from session 1 data were then used to predict session 1 data, as with the full set of data in the n = 15 analysis. The purpose of this was to evaluate how robust the derived function from only half the data set was prior to testing novel stimuli. Again, this analysis is most analogous to the training versus training performed by the neural network. Table 5 shows details of the cell performances. Using session 1 data (n = 8), correct classification dropped to 93.75% overall for the eye condition, and 96.88% on the workload tasks, but it was felt that performance was good enough to evaluate further testing on novel stimuli.

Correct classification of novel stimuli was 17.87% for the eye condition and 39.29% for the workload condition. Chance correct classification for the eight tasks would be 12.50%.

DISCRIMINANT ANALYSIS USING THE ALPHA BAND

Discriminant functions were also derived using only the alpha band. When the discriminant function is based only on alpha, changes occur in the ability to develop a discriminant function and the resulting capability to predict novel stimuli. Table 6 shows results of the discriminant analysis using only the alpha band.

Table 6.
Discriminant Analysis Table
Percent Correct Classification of Tasks Using Alpha Band, 4 Leads

N = 15

EYE

	CLOSED	OPEN	
COUNT	33.33 **5**	13.33 **2**	23.33
NO COUNT	86.67 **1**	33.33 **5**	60.00
	60.00	23.33	**41.66**

WORKLOAD

	DM	MP	
HIGH	60.00 **9**	26.67 **4**	43.34
LOW	60.00 **9**	33.33 **5**	30.16
	60.00	30.00	**40.87**

N = 8

EYE

	CLOSED	OPEN	
COUNT	50.00 **4**	25.00 **2**	37.50
NO COUNT	100.00 **8**	25.00 **2**	62.50
	75.00	25.00	**50.00**

WORKLOAD

	DM	MP	
HIGH	62.50 **5**	50.00 **4**	56.25
LOW	87.50 **7**	25.00 **2**	56.25
	75.00	37.50	**56.25**

N = 7

EYE

	CLOSED	OPEN	
COUNT	0.00 **0**	0.00 **0**	0.00
NO COUNT	85.71 **6**	14.29 **1**	50.00
	85.71	14.29	**50.00**

WORKLOAD

	DM	MP	
HIGH	28.57 **2**	28.57 **2**	28.57
LOW	28.57 **2**	28.57 **2**	28.57
	28.57	28.57	**28.57**

When only the alpha band is used to derive these discriminant functions, there is approximately a 50% reduction in the correct classification of workload tasks overall. The capability of predicting eye condition tasks, based on the derived function, for novel stimuli is essentially unchanged overall. However, eye tasks classification based on alpha was 0%, if the subjects were counting. But, if subjects' eyes were closed and there was no counting, discrimination based on alpha alone was very good (85.71%). These results are aligned with the arousal literature findings in studies using frequency analysis techniques referred to earlier in this study. Correct classification of these tasks by chance is 12.5%.

Interpretation of the sensitivity of the spectral analysis of the EEG is dependent on whether the subjects were performing the activity as directed. Verification of activity for the eye condition was based on subject report. In addition to subject report, mean time to respond (math processing), mean response time (display monitoring), and error rate were collected for the workload condition.

For all subjects, the math processing task, low difficulty level, was performed with a mean accuracy of 98.05%, with a standard error in the performance of 0.62%. The high level of that task had a mean accuracy of 97.13%, and a standard error of 0.63%. The display monitoring tasks were performed with a mean accuracy of 89.95%, with a standard error of 3.53%, and 92.67%, standard error = 3.96%, for the low and high levels respectively.

For the math processing tasks mean time to respond was 1050 ms, standard error = 194.8 ms for the low level and 2946 ms with a standard error of 314.9 ms for the high level. The low difficulty level of display monitoring had a response time of 3200 ms with a standard error of 1240 ms , while the high level response time was 3460 ms with a standard error of 480 ms.

NEURAL NETWORK

A back-propagated three layer perceptron was coded in "C" on a VAX. Initial layers of the network were set at 800 x 100 x 8. Raw data files were converted into separate neural network data files for training the network and to establish weights between the input layer and the hidden layer. Once these weights were established, the network was tested for its ability to classify one-second intervals of EEG time histories resulting from the eight tasks. Since this effort serves as an initial attempt for evaluating a neural network as an analysis tool, the length of the epoch T for spontaneous EEG to be analyzed was not well understood. Clinical applications use as much as T = five or ten seconds, whereas workload and psychophysiological applications may use several milliseconds for analysis for evoked potential. For this study, T = 1 second was chosen.

NEURAL NETWORK TRAINING

Neural Network Training Samples. One hundred, one-second intervals were randomly selected for each subject from each of the eight task time histories to serve as the neural network input for training. These intervals were chosen such that they were as far into the task as to be representative of the spontaneous response for that task. These samples were randomly selected from the records, excluding time segments with artifacts. Each one-second sample was represented by a 12-bit digital string from each of the four leads sampled at a rate of 200 HZ; the input vector was 1 x 800. Since the relationship of space-time patterns of neural activity to antecedent or consequent events are not well understood, a large dimensionality in the input vector insures that loss of information is minimized. The 100 one-second samples were collected randomly, without replacement, from the two trials for each task. That is, half of the training set was from the first session and half from the second session. The testing samples for the net were also 100, one-second slices from the EEG time histories collected by the same method.

The net was then trained on the data by initiating training passes. The network was set to perform not more that 2000 training passes of the training files. Each sample was assigned the task number label based on which task generated the signal. Every time a new sample signal from a task was input, the network adjusted its weights based on the similarity of the new sample signal with the previous sample signals having the same label. During learning, the output of the network for a particular input pattern is compared by its label to the desired output pattern established by previous input patterns. The difference between these two values propagates an error signal back through the network, iteratively. A cutoff score was set to define the acceptable difference between the actual and desired output. The error signal is filtered through the derivative of the sigmoid response of the processing units, and used to generate changes in the interconnection weights between layers. Training passes were made until the network reached the set number of passes, or reached the set cutoff score, which ended the training.

If the set cutoff score is reached by the end of the training passes, the net is said to have converged. Convergence essentially means that a unique pattern of weights has been established between the input layer and the hidden layer for each class of input patterns. In this case, each task type is a class. These weighted connections create patterns in the network's memory that can be used to classify either the data that created those patterns or novel stimuli presentations of the same signal type.

When trained, the net associated each sample with its task label, learned during training passes. Classification was made by activating one of the eight output nodes based on the test sample signal similarity to a trained signal. That is, when a test sample signal was most like a labeled sample of a trained signal, the appropriate output node is assigned a value of 1. The decision on which node to assign 1 is based on the weightings through the net. The remaining seven output nodes are assigned values of zero.

HIDDEN LAYER SEARCH

The original configuration of the network did not provide satisfactory performance. In fact, the network failed to converge at the 800 x 100 x 8 configuration. For this reason, a search was initiated to find an acceptable configuration to analyze the sets of novel stimuli and provide results demonstrating neural network capability to discriminate workload tasks based on the EEG signal. A systematic approach was defined to vary four network variables - the hidden layer size, alpha, beta, and the cutoff score . Alpha and beta are network variables which control the rate of learning and forgetting through the network connections. The cutoff score serves as the delta parameter.

<u>100 Node Hidden Layer Performance.</u> The original network configuration was initiated by setting the hidden layer = 100 nodes, alpha = 0.30, beta = 0.50, and the cutoff = 0.10. The 73 hours of CPU time had elapsed at the time of run termination. At that point the network had failed to converge.

At the time of termination, the actual value of the cutoff score had begun asymptotic behavior at a value of 0.21. This value was reached on the 350th training pass and continued to fluctuate for approximately 300 more passes. Based on this behavior, it was determined that a hidden layer of 100 nodes did not provide enough connections between the input layer and hidden layer to provide a unique pattern of weights. Further training at this size hidden layer was abandoned.

<u>Search Strategy.</u> The search for a hidden layer size was bounded between 100 and 400 nodes. Since the 100 node hidden layer did not converge, it was determined to increase the size of the hidden layer. In addition, based on general knowledge of neural network research, fairly sizable increments were used to prevent fruitless activity. The upper bounding at 400 was selected to prevent an over-generalization effect.

Data from one subject were used to find the best network performance. This data were selected based on an EEG time history that had minimal noise. Once a network was found that showed potential, other subjects' data were used to train and test that configuration. Table 7 shows the performance results of the various hidden layer trials.

Table 7.
Neural Network Hidden Layer Search

	Performance Percent Correct Classification		
Size	Training Set	Testing Set	CPU Time
100	no convergence	0%	73 hours
250	72.25%	28.13%	7 hours
300 *	81.35%	30.00%	5 hours
400	80.12%	21.35%	9 hours

250 Node Hidden Layer. The first alternative configuration was set at 250 nodes. This network converged in approximately seven hours of CPU time. This was a significant improvement over the 100 layer configuration. The net was tested using its own training set to evaluate its accuracy. The overall correct classification of the tasks was 72.25%. Only two of the tasks reached an accuracy of 90% or better. Although this accuracy rate indicated that the net had not achieved a good enough classification strategy, a testing set was run to evaluate its power to classify novel stimuli. The result of the run was a 28.13% correct classification of the novel stimuli. Chance correct classification of would have been 12.5%. Although performance of twice chance was not a major success, there was some indication that the neural network was showing some potential. Based on this result, it was determined to increase the hidden layer by only 50.

300 Node Hidden Layer. Performance of 81.35% correct classification of the training set was reached in approximately 5 hours CPU time. The testing set had a classification accuracy of 30% or almost three times chance. Because of the relatively small CPU time the 300 node hidden layer was selected to investigate the effect of variable manipulation of the neural network variables alpha, beta, and cutoff. Although the training vs. training was still not in the 90% range, performance was somewhat improved. Due to the limited understanding of neural networks, a larger node size might have degraded performance on novel stimuli rather than improve it. A 400 node hidden layer was also investigated. As can be seen in Table 7 this size hidden layer showed decreased performance.

SEARCH STRATEGY FOR CONTROL VARIABLES

At the 300 node hidden layer, variables alpha, beta, and the cutoff score were varied to determine their effect on correct classification. These variables were manipulated independently. They were increased and decreased by halving the distance between the original setting and 0. That distance was then added or subtracted to the variable. A network was then trained and tested at the new level. Table 8 shows performance rates of the net due to the variable manipulations.

Table 8.
Neural Network Variable Search

VARIABLE	VALUE	PERCENT CORRECT TRAINING	PERCENT CORRECT TESTING
	0.25	75.63	31.25
	0.50	81.38	30.00
BETA	0.75	65.50	32.50
	0.88*	90.63	36.25
	1.00	76.63	30.63
	0.15	69.38	30.63
ALPHA	0.30*	75.75	34.38
	0.45	68.12	30.00
	0.05*	90.63	36.25
CUTOFF	0.10	75.75	34.38
	0.15	72.90	25.22
	0.20	31.00	18.75

Beta was randomly selected as the first variable to change. Initial setting was 0.50, therefore, 0.25 was added or subtracted. Performance decreased with a beta of 0.25, so increases in beta were then evaluated. Beta increased performance until it was set equal to 1.00. A further halving of intervals between the best beta result at 0.75 and a reduced performance level of 1.00 was made to determine if any setting above 0.75 improved the net. The best performance was achieved when beta was set at 0.88.

Using the starter cutoff variable equal to 0.10, training vs. training had a classification accuracy of 75% and training vs testing achieved at 35% rate. At this point, the cutoff score was increased from 0.10 to 0.15 then to 0.20. Performance decreased for both training vs. training and training vs. testing as the cutoff variable increased. The variable was returned to the 0.10 level to investigate alpha effect and later decreased to 0.05 for the final network evaluations.

Alpha was initially set at 0.30. It was varied by a 0.15 increase and decrease. Both changes had negative impact on performance. Alpha was returned to its original setting of 0.30.

The final configuration of the network was at the hidden layer set at 300 nodes, alpha at 0.30, beta decreased to 0.88 and the cutoff score was set at 0.05. This configuration achieved the best training vs training and training vs testing classification accuracy of all networks evaluated at a rate of 90.63% and 36.25% respectively for the test subject.

NEURAL NETWORK TESTING

Once a final configuration of the net was selected, 160 one-second samples, 20 from each task, were used to test the network's capability to classify the eight conditions. The percentage of correctly classified tasks using novel stimuli determined the classification ability or sensitivity of the neural network of the EEG signal features. After the network was appropriately trained, a separate set of 160 one-second samples were used to test the network's ability to classify each treatment. Twenty samples were selected randomly, without replacement, from the remaining segments of each of the eight tasks. Half of the testing set was from the first session, and the other half from the second session. Each of the eight output nodes, representing the eight conditions, was assigned a "1" for match; "0 " for no match, in a binary coding strategy. That is, for a math processing task at high level, the network must activate the designated math processing-high node as 1, and 0 for all other nodes.

The 800 x 300 x 8 configuration was then used to train and test subjects. As with the discriminant analysis, one subject was dropped from the analysis due to noise in the signal. Results of the analysis are shown in Table 9. The cell accuracy percentages are the mean accuracies for all subjects. The confusion matrices on which these values were based can be found in Appendix G. This analysis is most analogous to the discriminant analyses using n = 15 and n = 7 as discussed in the discriminant analysis performance section.

Table 9.
Neural Network Analysis Table

TRAINING VERSUS TRAINING

EYE

	CLOSED	OPEN	
COUNT	86.17	72.83	79.50
NO COUNT	89.50	92.50	91.00
	87.83	82.66	**85.24**

WORKLOAD

	DM	MP	
HIGH	84.17	86.17	85.17
LOW	93.17	92.67	92.92
	88.67	89.42	**89.04**

TRAINING VERSUS TESTING

EYE

	CLOSED	OPEN	
COUNT	31.67	37.30	34.47
NO COUNT	30.83	38.33	34.58
	31.25	37.81	**34.53**

WORKLOAD

	DM	MP	
HIGH	32.50	34.17	33.33
LOW	33.33	35.83	34.60
	32.90	35.00	**33.95**

The training samples were used to develop the weighting of the connections between the input layers, hidden layer, and output layer. Recall that the output layer represented each of the eight conditions. For comparison purposes, this weighting can be thought of as analogous to developing a discriminant function. Once the training passes were through, the same set of data used to train the network was used to test its sensitivity to the tasks. As with the discriminant analysis, a confusion matrix was built to map actual tasks with guessed tasks. This enabled the identification of the percent correct classification along the main diagonal. The percent correct classification was then collapsed over all subjects into two by two cells. The resulting two by two cells for the overall performance across subjects for eye tasks and workload tasks are shown in Table 9. These results can be compared with the discriminant analysis results.

Inspection of Table 9 shows that using all the available features of the EEG time histories, the correctly classified the eye condition tasks 85.24% of the time. Workload conditions had a slightly better recognition at 89.04%.

Training versus Testing. When novel stimuli was presented to the trained net, performance dramatically decreased to an overall level of 34.24%. The net was fairly consistent in its ability to classify both eye condition tasks and workload condition tasks at a rate of 34.53% at 33.95%, respectively. These results can be compared to the performance differences of the discriminant analysis, where the correct classification of novel stimuli was 39% for workload condition tasks, and only 18% for eye condition tasks.

Within the eyes closed, no-counting condition,the network performed at the lowest recognition rate of 30.83%. But, the variability of performance across all tasks was small. Whereas, in the discriminant analysis, eyes open with counting had no correct classifications and the eyes-closed, no-counting, task had the 100% percent correct classification in the alpha band only discriminant analysis on the test set.

Workload tasks were classified with an overall accuracy of 33.95%. Display monitoring was classified with the lowest rate, 32.50% and math processing, low, was classified with the highest accuracy (35.83%). Overall classification using neural network of these tasks was fairly consistent overall with the discriminant analysis results at 33.95%.

IV. CONCLUSION

Techniques to measure and classify mental workload conditions and levels in real time are needed by Air Force programs developing decision aiding systems such as the Pilot's Associate. Monitoring and analyzing physiological parameters can provide information about the pilot's mental workload state to those systems. By monitoring a continuous signal such as the EEG and using this physiological response to mental effort imposed by a task, the system could infer the level of mental workload from the aspect of the physiological response to effort imposed by a task. However, current research does not provide a reliable method for systems such as Pilot's Associate to use to interpret EEG signals in terms of their relationships to mental workload tasks or levels. In an attempt to provide a reliable method for classifying EEG resulting from arousal and mental workload tasks, this study investigated the analysis capability of an artificial neural network.

The use of neural network analysis is more consistent with Freeman's (1988) hypotheses of brain functions. He suggested that what has been previously relegated to noise in the EEG may, in fact, be a reflection of the dynamically distributed activity characterized by a mean field intensity. He further argued that this activity reflects the integration mode of the brain and that these characteristics are nonlinear in nature. This information may be lost in transformation from the time to frequency domain. Based on this hypothesis of nonlinearity, it was hoped that neural networks might provide a better overall sensitivity since the algorithms used in neural networks make no assumptions of linearity. Also, in contrast to the current practice of FFT analysis, which loses information during the transformation of the EEG signal into the frequency domain, the full data features from the time series EEG traces could be used for the analysis.

In order to completely evaluate the neural network's capability, it was necessary to first analyze the FFT sensitivity with respect to the information it could provide about the mental workload conditions. The results of the statistical analysis of spectral features of the EEG traces in this study were fairly consistent with other studies which have used that technique (Gopher and Donchin, 1986; O'Donnell and Eggemeier, 1986). That is, the spectral features analyzed in this study were sensitive to distinct changes in workload between tasks, but not to levels of workload within a particular task. Alpha was noted to change with eye condition. The frontal, midline electrode, which is subject to facial and eye movement during the task, showed less sensitivity to alpha changes. When subjects counted, the desynchronization of the alpha band became apparent. The log power for alpha was no longer significant at any position. In fact, alpha changes, during counting tasks, accounted for none of the variability at the Fz and Oz positions. By contrast, it accounts for 11% at Pz, 20% at Cz, and 17% at Pz during eye closed, no-counting tasks. With respect to the value of analyzing the spectral features of the workload tasks (math processing and display monitoring), the difference in alpha log power was significant at Cz and Pz. However, the amount of variance accounted for in this case was only 5% and 6%. Task difficulty was not found to be significant ($p = 0.20$) at the 5% level of confidence. Using the ANOVA results one can determine if a lead was significant for a particular task, but a macro level interpretation or classification of tasks is not possible. Therefore, it may be concluded that analysis of the spectral features provides little information for designers to use for classification of workload states as would be necessary in a resource modelling module for the Pilot's Associate.

Although discriminant analysis of the log power is rarely used in the psychophysiological paradigm to analyze the EEG, discriminate analyses were applied to the log power values in this study and proved useful in categorizing workload activity. The advantage of developing a taxonomy of workload activity based on spectral features is that direct interpretation of the signal feature with respect to cognitive activity may not be necessary. Merely grouping EEG by task may have some value for application. The performance on the split data discrimination using all bands at all leads was 93.75% for the eye condition and 96.88% for the workload condition. This result must be met with some caution due to the tendency for a function to overgeneralize based on small sample size. Discriminability of the tasks was only 17.87% accuracy for eye condition and 43.34% for workload when the alpha band was used by itself. It can be inferred from this reduction that, although alpha band information has been used extensively in EEG research paradigms, the other bands significantly contribute to the ability to classify tasks. In this study the use of the discriminant analysis accomplished two things. First, it overlayed a multivariate clustering technique allowing categorization of tasks based on their spectral features. Second, it provided a way of more closely evaluating the sensitivity of the neural network.

The neural network configuration used in this study performed about the same or slightly better than the discriminant analysis using the spectral features. The percent correct classification by the neural network was 34.24% for novel stimuli over all conditions. Discriminant analysis of the spectral features provided an overall accuracy of 28.58% using all bands at all leads. It should also be noted that the performance level of the network was fairly consistent across conditions and between levels of difficulty within conditions. The spectral features were less sensitive between the difficulty levels of the tasks. While the neural network's sensitivity is not remarkable, considering the variability of the signals even within a subject, the findings are encouraging.

In summary, the neural network's performance was at least as good at classifying tasks as analysis using spectral features. But the judgement of whether or not they will provide a better analysis tool for EEG could not be made by the results of this study. A bounded, exhaustive search of combinations of the size of the hidden layer, and set values for the learning and forgetting parameters used in this study may provide better performance.

APPENDIX A

Subject Consent Form

SUBJECT CONSENT FORM

You are invited to participate in a study testing the usefulness of an artificial neural network as an analysis tool for EEG decoding. If you decide to participate, we will take measurements from your on-going brainwave activity during tasks. The skin on the scalp will be mildly abraded with an alcohol-soaked gauze pad and electrodes will be applied to the cleansed areas so that your brainwaves can be recorded.

You will be asked to perform tasks displayed on a TV screen. These tasks will be explained in more detail. All tasks have been used in previous research. You will be asked to perform wearing the electrodes. These are not cumbersome and will in no way interfere with your performance.

We will schedule a number of one to one and one half hour sessions for you over the next 30 days. The sequence of sessions will be scheduled according to your availability. You will have opportunities to take breaks as needed. If you experience eye strain during a session, we recommend that you look around the room and focus on different objects. If you feel yourself getting very bored or tired, please feel free to take a break. Please let us know if there is something wrong with the experiment. We are open to suggestions.

Your cooperation and motivated performance are essential to us. Therefore, we will be happy to answer any questions, so feel free to ask questions at any time. Captain Gretchen Lizza will be available to answer any of your questions. She may be reached at 429-5892. Also, Dr. Herb Colle, Dept. of Psychology may be consulted as well. His number is 873-6921.

Data collected in this study will be treated in such a way as to protect your privacy. Data will be published in scientific journals without identifying individual subjects. The general results of this study will be available to you upon request.

No alternative means exist to obtain the required information and data that this experimental design. You should incur no personal risk as a result of your participation. Your are free to withdraw from this experiment at any time. The experiment will last for a number of sessions, so please tell us during your first few sessions if you do not wish to complete the study.

volunteer's initials__________

APPENDIX B
Neural Network Information

BACKPROPOGATION ALGORITHM

The back-propagation training algorithm is an iterative gradient algorithm designed to minimize the mean square error between the actual output of a multilayer feed-forward perceptron and the desired output. It requires continuous differentiable non-linearities. Essentially the algorithm has four steps. It sets all weights and node offsets to small random values. Once a continuous valued input vector is presented and desired outputs are specified, the network can be used as a classifier. All desired outputs are typically set to zero except for that corresponding to the class of the input which is to 1. The input could be new on each trial or samples from a training set could be presented cyclically until weights stabilize. A sigmoid nonlinearity is used to calculate outputs. The weights are then adapted using a recursive algorithm starting at the output nodes and working back to the first hidden layer by the equation :

$$w_{ij}(t+1) = w_{ij}(t) = nd_j \; x_i \; .$$

In this equation $w_{ij}(t)$ is the weight from hidden node or from an input to node j at time t, x_i is either the output of node i or is an input, n is a gain term, and d_j is an error term for node j. If node j is an output node, then

$$d_j = y(1 - y_j)(d_j - y_j),$$

where d_j is the desired output of node j and u_j is the actual output. If node j is an internal hidden node, then

$$d_j = x_j(1 - x_j)\ d_k\ w_{jk}$$

where k is over all nodes in the layers above node j. Internal node thresholds are adapted in a similar manner by assuming they are connection weights on links from auxiliary constant-valued inputs. Convergence is sometimes faster if a momentum term is added and weight changes are smoothed.

APPENDIX C.
ANOVA Source Tables

Table C1.
Eye Condition ANOVA

For performance dependent variables and Alpha band variation:

SOURCE	SS	DF	MS	F
COUNTING (C)	SS(C)	c-1 1	$\frac{SS(C)}{DF(C)}$	$\frac{MS(C)}{MS(SxT)}$
EYE COND. (E)	SS(E)	e-1 1	$\frac{SS(E)}{DF(E)}$	$\frac{MS(E)}{MS(SxT)}$
SUBJECTS (S)	SS(S)	s-1 7	$\frac{SS(S)}{DF(S)}$	
(CxE)	SS(CxE)	(c-1)(e-1) 1	$\frac{SS(CxE)}{DF(CxE)}$	$\frac{MS(CxE)}{MS(SxT)}$
(ExS)	SS(ExS)	(e-1)(s-1) 7	$\frac{SS(ExS)}{DF(ExS)}$	
(CxS)	SS(CxS)	(c-1)(s-1) 7	$\frac{SS(CxS)}{DF(CxS)}$	
(CxSxE)	SS(CxExS)	(c-1)(e-1) (s-1) 7	$\frac{SxS(CxExS)}{DF(CxExS)}$	
[S x Treatment	*SS(ExS)+SS(CxS)* *+SS(CxExS)*	*SS(SxT)]* *(21)*	*21*	

Table C2.
Workload Condition ANOVA

For performance dependent variables and Alpha band variation:

SOURCE	**SS**	**DF**	**MS**	**F**
CTS TASK (T)	SS(T)	t-1 1	$\frac{SS(T)}{DF(T)}$	$\frac{MS(T)}{MS(TRxS)}$
DIFFICULTY (D)	SS(D)	d-1 1	$\frac{SS(D)}{DF(D)}$	$\frac{MS(D)}{MS(TRxS)}$
SUBJECTS (S)	SS(S)	s-1 7	$\frac{SS(S)}{DF(S)}$	
(TxD)	SS(TxD)	(t-1)(d-1) 1	$\frac{SS(TxD)}{DF(TxD)}$	$\frac{MS(TxD)}{MS(TRxS)}$
(DxS)	SS(ExS)	(d-1)(s-1) 7	$\frac{SS(DxS)}{DF(DxS)}$	
(TxS)	SS(CxS)	(t-1)(s-1) 7	$\frac{SS(TxS)}{DF(TxS)}$	
(TxDxS)	SS(TxDxS)	(t-1)(d-1) (s-1) 7	$\frac{SS(TxDxS)}{DF(TxDxS)}$	
[S x Treatment	*SS(TxS)+SS(DxS)* *+SS(DxTxS)*	*SS(TRxS)]* *(21)*	*21*	

APPENDIX D
Latin Squares Design

Subject	First Trial								Second Trial							
1	2	8	4	5	1	7	3	6	1	8	6	5	3	4	2	7
2	1	7	3	6	2	8	4	5	2	7	5	6	4	3	1	8
3	6	4	1	8	3	5	7	2	3	4	2	8	7	1	6	5
4	3	5	2	4	4	6	1	8	4	5	8	7	1	2	3	6
5	8	2	5	7	7	1	6	3	7	2	3	4	6	5	8	1
6	7	1	6	3	8	2	5	4	8	1	4	3	5	6	7	2
7	4	6	8	1	5	3	2	7	5	6	7	1	2	8	4	3
8	5	3	7	2	6	4	8	1	6	3	1	2	8	7	5	4
9	4	3	8	2	5	5	1	7	5	3	7	2	1	8	4	6
10	1	2	3	4	7	7	5	6	7	2	6	4	5	3	1	8
11	3	4	7	1	6	6	2	8	6	4	8	1	2	7	3	5
12	2	1	4	3	8	8	6	5	8	1	5	3	6	4	2	7
13	8	7	6	5	2	2	4	3	2	7	3	5	4	6	8	1
14	7	8	5	6	1	1	3	4	1	8	4	6	3	5	7	2
15	5	6	1	7	4	4	8	2	4	6	2	7	8	1	5	3
16	6	5	2	8	3	3	7	1	3	5	1	8	7	2	6	4

Key:
1 = no counting/eyes open
2 = no counting/eyes closed
3 = counting/eyes open
4 = counting/eyes closed
5 = math task/low workload
6 = math task/high workload
7 = probability monitoring/low workload
8 = probability monitoring/high workload

APPENDIX E
Digitization Information

DIGITIZATION

The analog records were digitized by the Neurophysiological Workload Test Battery (NTWB) computer. EEG signals are continuous variations of potential as a function of time. In order to digitize, the random variable must have only one set of discrete values at a set of discrete time instances. A 12 bit ensemble was used initially for input to the FFT analysis and the neural network. Lopes da Silva (1976) and Steineberg and Paine (1964) have found that most EEG analysis can be performed using 9 to 12 bits representing 512 to 4096 amplitude levels.

The sampling interval was 100 HZ. This rate is more than two times the Nyquist frequency (for this data a sampling rate of 60 HZ would be necessary to reconstitute the sample with fidelity).

APPENDIX F
Discriminant Analysis Confusion Matrices

Table F1.
Discriminant Analysis Using Alpha Band/4 Leads (N = 15)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	5	7	1	0	1	0	1	0
	33.33%	46.67%	6.67%	0.00%	6.67%	0.00%	6.67%	0.00%
EC/NC	1	13	0	1	0	0	0	0
	6.67%	86.67%	0.00%	6.67%	0.00%	0.00%	0.00%	0.00%
EO/C	0	0	2	4	1	3	1	4
	0.00%	0.00%	13.33%	26.67%	6.67%	20.00%	6.67%	26.67%
EO/NC	0	0	1	5	1	6	1	1
	0.00%	0.00%	6.67%	33.33%	6.67%	40.00%	6.67%	6.67%
DM/H	0	1	0	2	9	2	0	1
	0.00%	6.67%	0.00%	13.33%	60.00%	13.33%	0.00%	6.67%
DM/L	0	0	1	0	2	9	0	3
	0.00%	0.00%	6.67%	0.00%	13.33%	60.00%	0.00%	20.00%
MP/H	0	0	0	0	4	2	4	5
	0.00%	0.00%	0.00%	0.00%	26.67%	13.33%	26.67%	33.33%
MP/L	0	2	0	1	3	2	2	5
	0.00%	13.33%	0.00%	6.67%	20.00%	13.33%	13.33%	33.33%
TOTAL	6	23	5	13	21	24	9	19
	10.71%	41.07%	8.93%	23.21%	37.50%	42.86%	16.07%	33.93%

EC = Eyes Closed
EO = Eyes Open
DM = Display Monitoring
MP = Math Processing

C = Counting
NC = Not Counting
H = High
L = Low

Table F2.
Discriminant Analysis Using 4 Bands/4 Leads (N = 15)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	15	0	0	0	0	0	0	0
	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
EC/NC	0	15	0	0	0	0	0	0
	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
EO/C	0	0	15	0	0	0	0	0
	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%
EO/NC	0	0	0	15	0	0	0	0
	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%
DM/H	0	0	0	0	15	0	0	0
	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%
DM/L	0	0	0	0	0	15	0	0
	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%
MP/H	0	0	0	0	0	0	15	0
	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
MP/L	0	0	0	0	0	0	0	15
	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%
TOTAL	15	15	15	15	15	15	15	15
	26.79%	26.79%	26.79%	26.79%	26.79%	26.79%	26.79%	26.79%

EC = Eyes Closed
EO = Eyes Open
DM = Display Monitoring
MP = Math Processing

C = Counting
NC = Not Counting
H = High
L = Low

Table F4.
Discriminant Analysis Using 4 Bands/4 Leads (N = 8)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	7	0	0	0	0	1	0	0
	87.50%	0.00%	0.00%	0.00%	0.00%	12.50%	0.00%	0.00%
EC/NC	0	7	0	0	0	0	1	0
	0.00%	87.50%	0.00%	0.00%	0.00%	0.00%	12.50%	0.00%
EO/C	0	0	8	0	0	0	0	0
	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%
EO/NC	0	0	0	8	0	0	0	0
	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%
DM/H	0	0	0	0	8	0	0	0
	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%
DM/L	0	0	0	0	0	8	0	0
	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%
MP/H	0	0	0	0	0	1	7	0
	0.00%	0.00%	0.00%	0.00%	0.00%	12.50%	87.50%	0.00%
MP/L	0	0	0	0	0	0	0	8
	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%
TOTAL	7	7	8	8	8	10	8	8
	12.50%	12.50%	14.29%	14.29%	14.29%	17.86%	14.29%	14.29%

EC = Eyes Closed
EO = Eyes Open
DM = Display Monitoring
MP = Math Processing

C = Counting
NC = Not Counting
H = High
L = Low

Table F5.
Discriminant Analysis Using Alpha Band/4 Leads (N = 7)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	0	6	0	0	0	0	1	0
	0.00%	85.71%	0.00%	0.00%	0.00%	0.00%	14.29%	0.00%
EC/NC	0	6	0	0	1	0	0	0
	0.00%	85.71%	0.00%	0.00%	14.29%	0.00%	0.00%	0.00%
EO/C	1	0	0	1	1	0	2	2
	14.29%	0.00%	0.00%	14.29%	14.29%	0.00%	28.57%	28.57%
EO/NC	0	1	0	1	1	2	0	2
	0.00%	14.29%	0.00%	14.29%	14.29%	28.57%	0.00%	28.57%
DM/H	0	0	0	2	2	1	1	1
	0.00%	0.00%	0.00%	28.57%	28.57%	14.29%	14.29%	14.29%
DM/L	1	0	1	0	0	2	2	1
	14.29%	0.00%	14.29%	0.00%	0.00%	28.57%	28.57%	14.29%
MP/H	0	0	0	0	0	1	2	4
	0.00%	0.00%	0.00%	0.00%	0.00%	14.29%	28.57%	57.14%
MP/L	0	1	0	1	1	1	1	2
	0.00%	14.29%	0.00%	14.29%	14.29%	14.29%	14.29%	28.57%
TOTAL	2	14	1	5	6	7	9	12
	3.57%	25.00%	1.79%	8.93%	10.71%	12.50%	16.07%	21.43%

EC = Eyes Closed
EO = Eyes Open
DM = Display Monitoring
MP = Math Processing

C = Counting
NC = Not Counting
H = High
L = Low

Table F6.
Discriminant Analysis Using 4 Bands/4 Leads (N = 7)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	2	3	0	1	0	0	0	1
	28.57%	42.86%	0.00%	14.29%	0.00%	0.00%	0.00%	14.29%
EC/NC	1	2	0	0	1	0	1	2
	14.29%	28.57%	0.00%	0.00%	14.29%	0.00%	14.29%	28.57%
EO/C	0	0	0	0	1	0	0	6
	0.00%	0.00%	0.00%	0.00%	14.29%	0.00%	0.00%	85.71%
EO/NC	0	0	0	1	1	1	1	3
	0.00%	0.00%	0.00%	14.29%	14.29%	14.29%	14.29%	42.86%
DM/H	1	0	0	2	2	1	0	1
	14.29%	0.00%	0.00%	28.57%	28.57%	14.29%	0.00%	14.29%
DM/L	0	0	0	1	1	1	1	3
	0.00%	0.00%	0.00%	14.29%	14.29%	14.29%	14.29%	42.86%
MP/H	0	0	0	1	0	1	2	3
	0.00%	0.00%	0.00%	14.29%	0.00%	14.29%	28.57%	42.86%
MP/L	0	0	0	1	0	0	0	6
	0.00%	0.00%	0.00%	14.29%	0.00%	0.00%	0.00%	85.71%
TOTAL	4	5	0	7	6	4	5	25
	7.14%	8.93%	0.00%	12.50%	10.71%	7.14%	8.93%	44.64%

EC = Eyes Closed
EO = Eyes Open
DM = Display Monitoring
MP = Math Processing

C = Counting
NC = Not Counting
H = High
L = Low

APPENDIX G
Neural Network Analysis Confusion Matrices

Table G1.
Neural Network - Training Set Analysis (Subject 1)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	86	4	3	0	1	1	1	4
EC/NC	1	89	5	0	0	1	0	4
EO/C	0	0	99	0	0	0	0	1
EO/NC	0	1	10	78	0	3	3	5
DM/H	0	1	9	0	88	0	0	2
DM/L	0	1	4	0	0	93	0	2
MP/H	0	0	3	0	0	0	97	0
MP/L	0	0	4	0	1	0	0	95

Composite Accuracy (%): 90.63

EC = Eyes Closed C = Counting
EO = Eyes Open NC = Not Counting
DM = Display Monitoring H = High
MP = Math Processing L = Low

Table G2.
Neural Network - Testing Set Analysis (Subject 1)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	45	15	5	0	5	0	10	20
EC/NC	0	35	10	10	5	20	5	15
EO/C	15	10	35	15	15	0	5	5
EO/NC	20	5	5	30	5	15	10	10
DM/H	5	10	10	10	40	5	10	10
DM/L	20	10	10	10	5	25	5	15
MP/H	5	10	15	0	0	5	45	20
MP/L	0	15	15	15	10	0	10	35

Composite Accuracy (%): 36.25

EC = Eyes Closed C = Counting
EO = Eyes Open NC = Not Counting
DM = Display Monitoring H = High
MP = Math Processing L = Low

Note. Rows indicate the actual experimental condition; columns indicate the condition output by the neural network

Table G3.
Neural Network - Training Set Analysis (Subject 2)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	49	10	0	5	15	10	1	10
EC/NC	0	95	0	0	5	0	0	0
EO/C	0	9	44	5	21	10	6	5
EO/NC	0	0	0	99	0	0	1	0
DM/H	0	0	0	1	98	1	0	0
DM/L	0	0	0	1	3	96	0	0
MP/H	0	1	0	2	4	4	88	1
MP/L	0	0	0	1	0	2	0	97

Composite Accuracy (%): 83.25

EC = Eyes Closed
EO = Eyes Open
DM = Display Monitoring
MP = Math Processing
C = Counting
NC = Not Counting
H = High
L = Low

Table G4.
Neural Network - Testing Set Analysis (Subject 2)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	10	15	5	20	15	5	15	15
EC/NC	5	40	10	5	30	5	0	10
EO/C	5	20	15	10	30	10	5	5
EO/NC	5	10	0	35	0	15	15	15
DM/H	5	10	0	10	40	10	15	10
DM/L	5	10	15	0	25	40	0	5
MP/H	5	10	5	10	25	5	25	15
MP/L	5	10	5	0	30	10	0	40

Composite Accuracy (%): 33.75

EC = Eyes Closed
EO = Eyes Open
DM = Display Monitoring
MP = Math Processing
C = Counting
NC = Not Counting
H = High
L = Low

Table G5.
Neural Network - Training Set Analysis (Subject 3)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	49	2	12	16	10	4	3	4
EC/NC	0	87	5	3	5	0	0	0
EO/C	0	0	98	1	1	0	0	0
EO/NC	1	0	0	96	2	1	0	0
DM/H	0	0	2	3	95	0	0	0
DM/L	0	0	2	3	5	88	0	2
MP/H	1	0	13	6	12	1	64	3
MP/L	0	0	5	5	10	3	0	77

Composite Accuracy (%): 81.75

EC - Eyes Closed
EO - Eyes Open
DM - Display Monitoring
MP - Math Processing

C - Counting
NC - Not Counting
H - High
L - Low

Table G6.
Neural Network - Testing Set Analysis (Subject 3)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	25	10	10	30	5	5	0	15
EC/NC	15	20	15	15	15	0	10	10
EO/C	5	5	50	10	20	10	0	0
EO/NC	10	0	20	40	15	5	0	10
DM/H	0	10	20	15	30	5	15	5
DM/L	5	15	0	20	0	30	15	15
MP/H	0	10	25	25	20	5	10	5
MP/L	10	30	5	10	5	10	5	25

Composite Accuracy (%): 31.88

EC - Eyes Closed
EO - Eyes Open
DM - Display Monitoring
MP - Math Processing

C - Counting
NC - Not Counting
H - High
L - Low

Table G7.
Neural Network - Training Set Analysis (Subject 4)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	47	4	10	18	10	4	3	4
EC/NC	0	89	3	3	5	0	0	0
EO/C	0	1	97	1	1	0	0	0
EO/NC	1	0	0	93	4	1	1	0
DM/H	2	0	0	3	94	1	0	0
DM/L	0	0	2	2	6	87	1	2
MP/H	1	0	12	7	10	3	60	7
MP/L	0	0	4	6	9	4	0	77

Composite Accuracy (%): 80.50

EC = Eyes Closed
EO = Eyes Open
DM = Display Monitoring
MP = Math Processing

C = Counting
NC = Not Counting
H = High
L = Low

Table G8.
Neural Network - Testing Set Analysis (Subject 4)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	35	0	10	25	10	5	0	15
EC/NC	15	0	10	10	15	20	15	15
EO/C	50	10	20	10	0	0	5	5
EO/NC	10	0	20	40	10	0	5	15
DM/H	30	5	15	5	15	20	10	0
DM/L	20	0	15	5	30	40	15	0
MP/H	5	10	5	20	0	10	25	25
MP/L	25	5	10	5	5	10	10	30

Composite Accuracy (%): 33.75

EC = Eyes Closed
EO = Eyes Open
DM = Display Monitoring
MP = Math Processing

C = Counting
NC = Not Counting
H = High
L = Low

Table G9.
Neural Network - Training Set Analysis (Subject 5)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	63	3	10	1	4	0	8	11
EC/NC	0	85	4	0	0	0	7	4
EO/C	0	1	98	0	0	0	1	0
EO/NC	0	0	2	93	0	0	4	1
DM/H	0	0	3	0	89	0	7	1
DM/L	0	0	4	0	1	83	8	4
MP/H	0	1	0	0	0	0	99	0
MP/L	0	0	1	0	0	0	0	99

Composite Accuracy (%): 88.63

EC - Eyes Closed
EO - Eyes Open
DM - Display Monitoring
MP - Math Processing

C - Counting
NC - Not Counting
H - High
L - Low

Table G10.
Neural Network - Testing Set Analysis (Subject 5)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	35	10	15	15	10	0	5	10
EC/NC	0	30	5	25	10	5	10	15
EO/C	0	10	35	5	10	25	10	5
EO/NC	0	5	10	25	5	10	20	25
DM/H	0	10	0	10	55	10	15	0
DM/L	5	15	15	15	0	30	10	10
MP/H	5	5	5	5	15	0	45	20
MP/L	15	0	10	10	15	5	5	40

Composite Accuracy (%): 36.88

EC - Eyes Closed
EO - Eyes Open
DM - Display Monitoring
MP - Math Processing

C - Counting
NC - Not Counting
H - High
L - Low

Table G11.
Neural Network - Training Set Analysis (Subject 6)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	97	0	0	1	0	1	0	1
EC/NC	6	85	0	1	3	3	0	2
EO/C	8	0	68	3	4	5	1	11
EO/NC	1	0	0	95	3	1	0	0
DM/H	2	0	0	0	94	1	0	3
DM/L	5	0	0	0	1	93	0	1
MP/H	8	0	0	0	1	1	3	83
MP/L	4	0	0	1	2	1	0	92

Composite Accuracy (%): 88.38

EC - Eyes Closed　　C - Counting
EO - Eyes Open　　NC - Not Counting
DM - Display Monitoring　　H - High
MP - Math Processing　　L - Low

Table G12.
Neural Network - Testing Set Analysis (Subject 6)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	45	0	10	15	5	15	0	10
EC/NC	5	45	0	10	10	10	5	15
EO/C	25	15	25	10	5	0	10	10
EO/NC	15	10	5	45	0	5	5	15
DM/H	15	15	15	0	30	5	5	15
DM/L	5	0	0	35	5	30	5	20
MP/H	20	5	5	0	5	5	40	20
MP/L	5	5	5	20	15	10	10	30

Composite Accuracy (%): 36.88

EC - Eyes Closed　　C - Counting
EO - Eyes Open　　NC - Not Counting
DM - Display Monitoring　　H - High
MP - Math Processing　　L - Low

Table G13.
Neural Network - Training Set Analysis (Subject 7)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	93	0	1	1	0	0	1	4
EC/NC	3	76	6	3	3	0	3	6
EO/C	0	0	98	0	0	0	1	1
EO/NC	0	0	1	98	1	0	0	0
DM/H	3	0	4	0	91	1	1	0
DM/L	1	0	5	3	0	84	3	4
MP/H	1	0	1	0	0	0	96	2
MP/L	0	1	2	1	0	0	0	96

Composite Accuracy (%): 91.50

EC = Eyes Closed
EO = Eyes Open
DM = Display Monitoring
MP = Math Processing

C = Counting
NC = Not Counting
H = High
L = Low

Table G14.
Neural Network - Testing Set Analysis (Subject 7)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	40	0	0	10	5	5	25	15
EC/NC	5	20	15	10	25	5	15	5
EO/C	20	0	35	10	20	5	5	5
EO/NC	25	15	5	25	15	0	15	0
DM/H	20	5	5	10	35	15	5	5
DM/L	10	10	15	5	5	45	10	0
MP/H	5	5	5	10	5	10	40	20
MP/L	5	10	15	20	0	0	5	45

Composite Accuracy (%): 36.25

EC = Eyes Closed
EO = Eyes Open
DM = Display Monitoring
MP = Math Processing

C = Counting
NC = Not Counting
H = High
L = Low

Table G15.
Neural Network - Training Set Analysis (Subject 8)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	97	0	1	0	1	0	1	0
EC/NC	0	98	1	1	0	0	0	0
EO/C	0	0	98	0	0	1	1	0
EO/NC	2	0	1	96	0	1	0	0
DM/H	0	2	3	5	88	0	2	0
DM/L	0	13	6	12	1	64	3	1
MP/H	0	0	1	0	2	0	97	0
MP/L	0	1	2	1	0	0	0	96

Composite Accuracy (%): 91.75

EC = Eyes Closed C = Counting
EO = Eyes Open NC = Not Counting
DM = Display Monitoring H = High
MP = Math Processing L = Low

Table G16.
Neural Network - Testing Set Analysis (Subject 8)

	EC/C	EC/NC	EO/C	EO/NC	DM/H	DM/L	MP/H	MP/L
EC/C	10	15	5	20	15	5	15	15
EC/NC	5	20	15	10	25	5	15	5
EO/C	20	0	35	10	20	5	5	5
EO/NC	5	0	10	25	25	10	5	20
DM/H	10	10	0	0	55	0	10	15
DM/L	15	15	15	5	0	30	10	10
MP/H	5	5	15	0	0	20	45	5
MP/L	10	15	5	5	15	0	10	40

Composite Accuracy (%): 34.38

EC = Eyes Closed C = Counting
EO = Eyes Open NC = Not Counting
DM = Display Monitoring H = High
MP = Math Processing L = Low

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